Submovement overlap as a measure of movement smoothness

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Abstract. Many measures have been employed to quantify an aspect of healthy, skilled movement, which has been termed "movement smoothness" of which jerk is the most common. We propose a new, biologically-motivated quantification of "movement smoothness": submovement overlap.

In previous work, changes in submovements have been linked to changes in movement smoothness. Further investigation revealed that in stroke patients, submovements consistently tend to grow closer over the course of recovery. While jerk analysis showed some patients' movements growing significantly less smooth, submovement blending provided a remarkably consistent metric of recovery, despite wide variations in subject age, lesion territory, and stroke severity.

In stroke patients, it is not average jerk but submovement blending that meaningfully quantifies the movement smoothing that accompanies recovery. The strength and consistency with which it quantified patients' recovery indicates that analysis of submovement overlap may be a useful tool for measuring learning or other changes in motor behavior in future human movement studies.

1. Introduction

Quantification of movement smoothness has been pursued for a number of reasons. It has been investigated as an indicator of motor skill and coordination (Platz et al., 1994) and as an objective measure of recovery from neurological injury (Trombly, 1993; Cirstea & Levin, 2000; Kahn et al., 2001; Rohrer et al., 2002). Smoothness has been used to identify pre-symptomatic individuals with Huntington's disease (Smith et al., 2000) and has also been shown to account for the two-thirds power law, widely considered an invariant in human movement (Wann et al., 1988; Gribble & Ostry, 1996; Todorov & Jordan, 1998; Schaal & Sternad, 2001).

Many measures of movement smoothness have been used. Jerk, the third time derivative of position, is the most common of such measures (Flash & Hogan, 1985), but others include snap, the derivative of jerk (Edelman & Flash, 1987), and counting peaks in tangential velocity (Brooks, 1973; Fetters & Todd, 1987).

In simulations of movement made in the presence of signal-dependent noise, Harris and Wolpert (1998) showed that smooth point-to-point movements minimize endpoint error. While smoothness is a characteristic of healthy, mature human movement, the earliest movements made by infants (Hofsten, 1991) and by patients recovering from stroke (Krebs et al., 1998) are striking in that they initially *lack* smoothness but become more smooth with time. Any comprehensive model of movement production must describe not only the smoothness of movement, but also its non-smoothness during development and neurological recovery. This prompted our work in quantifying movement smoothness as a measure of stroke recovery, using both a jerk-based measure and submovement overlap.

2. Smoothness as low jerk

Thirty one patients of various ages, levels of impairment, and times post-stroke participated in therapy using rehabilitation robots, MIT-MANUS and InMotion2. A key characteristic of both robots is their backdrivability, that is, their ability to get out of the way when pushed by a subject. Thus, subjects' movements were minimally obscured by the dynamics of the robots. All movements discussed here were point-to-point movements, made while the robots were unpowered and hence acting only as passive measurement devices that restricted patients hand motion to a horizontal plane.

A jerk-based smoothness measures was used to analyze patients' movements. Qualitative observations of patients' movements growing smoother were not all reflected in the jerk-based measure did not. Rather, jerk-based smoothness significantly *decreased* in 10 of the 31 patients. This, despite the fact that all 10 patients had experienced recent strokes and therefore constituted the population expected to improve at the highest rate. These results are presented in their entirety in (Rohrer et al., 2002).
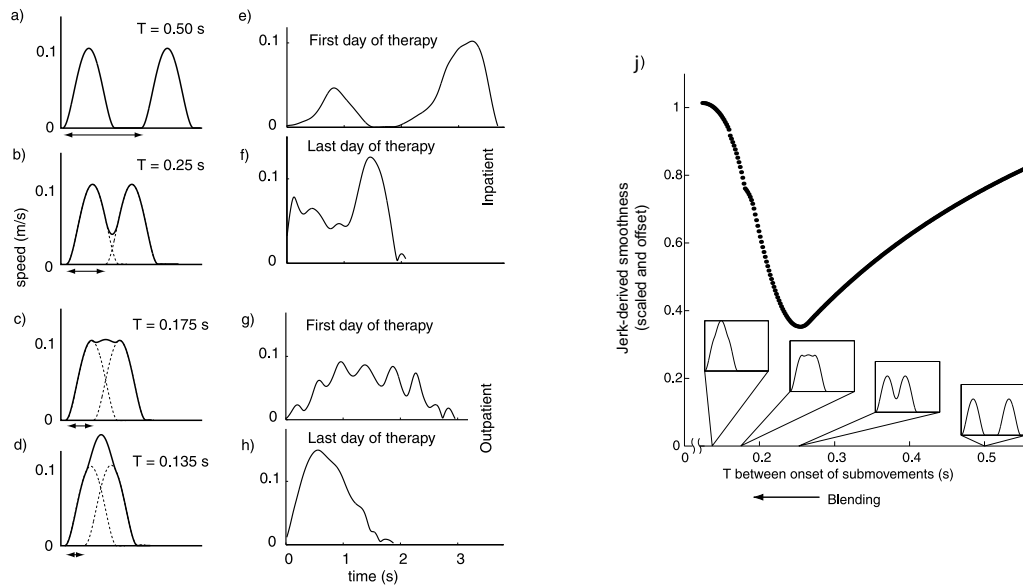
Figure 1. Simulated vs. actual speed profiles. a)-d) Progressive blending of two minimum-jerk curves at various states of blending (T). e)-h) Actual subject speed profiles. e) and f) are taken from the first and last therapy sessions of a subject with a recent stroke and g) and h) are taken from the first and last therapy sessions of an subject with a stroke of more than one year prior. Simulated speed profiles qualitatively resemble the actual subject data. a) contains two distinct speed peaks, just as the subject speed profile e). Continuing down the columns, b) and f) are qualitatively similar, c) somewhat resembles g), and d) is similar to h). Progression from the first to the last therapy sessions qualitatively suggests an increase in submovement blending. Also, the movements of the subject that is longer post-stroke have characteristics of more highly blended submovements, compared to those of the subject with a more recent stroke. j) Fluctuation of a jerk-based smoothness metric during the simulated blending of two simulated submovements. The values of the jerk metric are shown for a range of values of T. Translation to the left along the x-axis represents an increase in submovement blending. Translation up the y-axis represents an increase in jerk-based smoothness. Speed profiles for selected values of T are shown along the horizontal axis, depicting the state of the simulation at various degrees of blending. During submovement blending, the jerk metric first shows the movement growing less smooth before it begins to grow more smooth. Reproduced in part from (Rohrer et al., 2002).

3. Smoothness as overlapped submovements

We also applied a novel smoothness measure to the data: submovement overlap. Submovements are hypothesized, discrete elements of human movement. Observations of slow movements (Vallbo & Wessberg, 1993), eye saccades (Collewijn et al., 1988), cyclical movements (Woodworth, 1899; Crossman & Goodeve, 1983; Doeringer, 1999), ballistic movements (Morasso, 1981), and movements requiring a high degree of accuracy (Milner, 1992) all support the existence of submovements. Complex movements have been decomposed into submovements as an analysis tool (Morasso & Mussa-Ivaldi, 1982; Flash & Henis, 1991; Berthier, 1996; Burdet & Milner, 1998; Rohrer & Hogan, 2003) with apparent success.

The observation of Krebs et al. (1998) that movements made by patients recovering from stroke become smoother with recovery was originally attributed to a progressive overlapping and blending of submovements, though only isolated examples of submovement blending were reported. Further motivation for this analysis was provided by the data presented in (Rohrer et al., 2002), a sample of which is shown in Figure 1a-h. These data illustrate how the typical changes in patient speed profiles over the course of recovery closely match the changes observed in a submovement-based model of recovery.

In order to determine the role of submovements in movement smoothness,we performed a second analysis on the stroke recovery data, applying a novel submovement extraction algorithm (Rohrer et al., 2003). Movements from the first and last days of therapy are shown in Figure 2, together with their extracted submovements. The
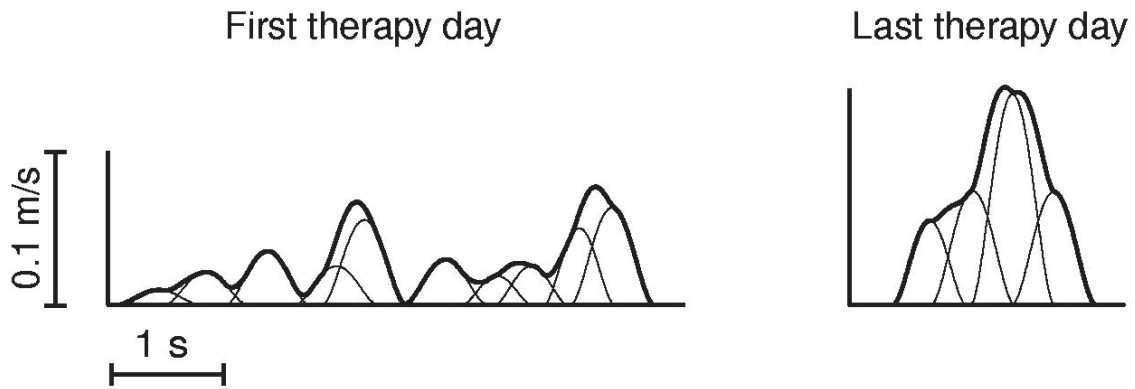
First therapy day   Last therapy day

Figure 2. Movements, with their extracted submovements, from the first and last days of therapy for a single patient. The pattern observed is typical: submovements grow higher in peak speed, longer in duration, fewer in number, and more overlapped. Reproduced from (Rohrer et al., 2004).

pattern displayed is typical: submovements grew higher in peak speed, longer in duration, fewer in number, and more overlapped. Of these trends, the increase in overlap most strongly influences the resulting smoothness of movement. This analysis showed that in stroke patients, submovements consistently tended to grow closer over the course of recovery; no patient's movements grew significantly less smooth, as measured by submovement overlap.

4. Discussion

The differences between jerk-based smoothness and submovement blending-based smoothness can be seen in Figure 1j, which displays the jerk-based smoothness calculated during simulated submovement blending. As the two submovements draw closer together, the jerk-based measure reports that the overall movement grows *less* smooth. This trend reverses after the two submovements are sufficiently blended ($T < 0.25s$) and the two measures begin to agree. This provides an explanation for the results of the jerk-based smoothness analysis reported earlier: the patients for which it reported movements growing less smooth were also the patients with the least amount of submovement overlap, patients with recent strokes. The simulation correctly predicts that, as these patients' submovements blended together, the jerk-based measure would interpret the movement as becoming less smooth.

In this analysis, jerk does not accurately reflect the increases in smoothness observed during the recovery process. There are other possible jerk-based smoothness metrics, of course. The fact that this particular metric did not perform well in this application does not indicate that there is no value in jerk-based smoothness measurement. However, it does suggest caution when measuring smoothness with jerk, as it can be misleading.

Recent work has shown that signal-dependent noise provides a biologically-grounded explanation for the ubiquitous observation that smoothness in the minimum-jerk sense accurately describes coordinated movement (Harris & Wolpert, 1998). However, we show here that recovery from stroke has more "fine structure", well-described by submovements. Whether a process like signal-dependent noise or optimal feedback control (Todorov & Jordan, 2002) can give rise to observed submovement behavior remains to be seen.

The counter-intuitive behavior of the jerk metric suggests that, at least during post-stroke recovery, jerk-minimization may not be the primary criterion governing refinements in movement patterns. Submovement overlap, however, captures qualitative observations of movement changes and provides a robust quantitative measure of the recovery process.

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